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# LEARNING PROCESSES AND LEARNING OUTCOMES


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This paper summarizes our present knowledge and understanding of the processes and outcomes of learning. The basic idea about learning is that the outcomes of learning (e.g., propositional knowledge, procedural skills, mental models) reflect differences in learning processes (e.g., encoding skills, attention allocation, hypothesis generation). Additionally, learning outcomes reflect differences in conative processes, (e.g., encoding skills, attention allocation, hypothesis generation). Additionally, learning outcomes reflect differences in conative processes, knowledge structures, and metacognitive skills, mediated by the learning processes. Against the background of a brief historical introduction, this article presents a research-based overview of the major categories of educationally relevant learning outcomes and of the underlying acquisition processes. In this perspective, different learning environments are discussed such as learning by direct instruction, drill and practice, and discovery. Finally, implications for the design of computerized instructional environments are indicated.

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# PREFACE

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# LEARNING PROCESSES AND LEARNING OUTCOMES


## SUMMARY

This paper outlines a functional model of learning with respect to initial states of learners, learning processes, and desired learning outcomes. The basic idea about learning is that the outcomes of learning (e.g., propositional knowledge, procedural skills, mental models) reflect differences in learning processes (e.g., encoding skills, attention allocation, hypothesis generation). Learning outcomes also reflect differences in conative processes, knowledge structures, and metacognitive skills, mediated by the learning processes. Following a brief historical introduction, educationally relevant learning processes and underlying acquisition processes are presented in terms of recent research findings. Different learning environments are discussed (e.g., direct instruction, drill and practice, and discovery), as well as implications for the design of computerized instructional environments.


## INTRODUCTION

Instructional psychology has emerged as an important and separate part of mainstream cognitive psychology. What has prompted this development? For the past 20 years, cognitive research has focused on the analysis of expertise including studies of memory, problem solving, and language (see, for example, Anderson, 1981; Dillon & Schmeck, 1983; Kanfer, Ackerman, & Cudeck, 1989; Nickerson, Perkins, & Smith, 1985; Sternberg, 1977). But just studying the nature of performance and the outcomes of learning without applying these findings to instruction is remiss. In other words, simply knowing how experts perform, and what they learn does not necessarily help in formalizing a way to transition novices to the same place (i.e., the best teaching approach to achieve the best learning outcome). But during the past 10 years, a new stream of research has appeared highlighting the transition issue. This research involves developing intelligent computer-assisted instruction (ICAI). Within this field, cognitive diagnosis has become critically important (e.g., Mandel & Lesgold, 1988; Sleeman & Brown, 1982; Wenger, 1987). In fact, accurate cognitive diagnosis and appropriate remediation provide the active ingredients in the transformation of instructional psychology from an art into a science.

Individuals come to any new learning task with differing profiles of knowledge, skills, and traits (i.e., individual difference measures). The "intelligence" in an ICAI (or the "mastery" in a master teacher) resides in the ability to analyze learner characteristics dynamically, using principles to decide what to do next and to adapt instruction to different learners (e.g., Sleeman & Brown, 1982; Wenger, 1987). Valid and reliable cognitive diagnoses, then, are essential to computer systems that adapt to their users' needs. But what should computers assess in order to contribute to a science of instruction?

According to prominent researchers in the field (e.g., Glaser, 1976; 1984; Glaser & Bassock, 1989; Snow, 1990), there are three main elements to a theory of instruction: (a) Analysis of the initial state of knowledge and skill; (b) Description of the desired or end state of knowledge and skill (learning outcome); and (c) Explanation of the learning processes that serve to transition a learner from initial to desired state accomplished in instructional settings. The point of instructional psychology, then, is to figure out how these elements relate to one another and how to enhance learning outcome with the appropriate instructional method.

The purpose of this article is to systematically explore possible relations among initial states, learning processes, and learning environment on various learning outcome measures, and to relate all these elements into a model of learning. This experimental method has, in the past, been referred to as aptitude-treatment interaction (ATI) research (see Cronbach & Snow, 1977) where *aptitude* is defined in the broadest sense of a person's incoming knowledge, skills, and personality traits. *Treatment* refers to the condition or environment that supports learning. The point of ATI research is to provide information about initial learner states that influence learning processes, which in turn can be used to select the best learning environment for a particular student to optimize outcome. To justify such an approach, evidence is needed that individuals do perform better or worse under different learning conditions (or environments). Two studies will be presented which illustrate ATI's following the discussion on each major area of this article: initial states, learning processes, learning outcomes, and learning environment.

A simple theoretical framework to guide research in this field is shown in Figure 1. The framework asserts that learning processes, influenced by the initial states of the learner, affect learning outcome. What is not represented in this figure, but will be shown later, is that learning environments also influence learning outcome. This impact may be direct, or may interact with characteristics of the learner to effect learning outcome.

## INITIAL STATES

Conative and cognitive aptitudes represent two basic determinants of learning and performance; what the learner brings to the learning task. *Conative* aptitudes refer to mental conditions or behaviors directed toward some event and include, for example, motivation, effort, volition, arousal, and striving (Kanfer, 1989; Revelle, 1989; Snow, 1989; Watson, Clark, & Tellegen, 1988). *Cognitive* aptitudes refer to mental processes and structures associated with knowledge and skill acquisition, such as the ability to encode, store, and retrieve information to and from memory (Anderson, 1983; 1987; Kyllonen & Christal, 1989). One distinction which is commonly made between these two factors is that the conative aptitudes, in general, are more malleable than the cognitive aptitudes, which tend to represent more stable or fixed abilities (e.g., Baron, 1985). Figure 2 represents an elementary depiction of the initial states with arrows implying possible direction of influence.

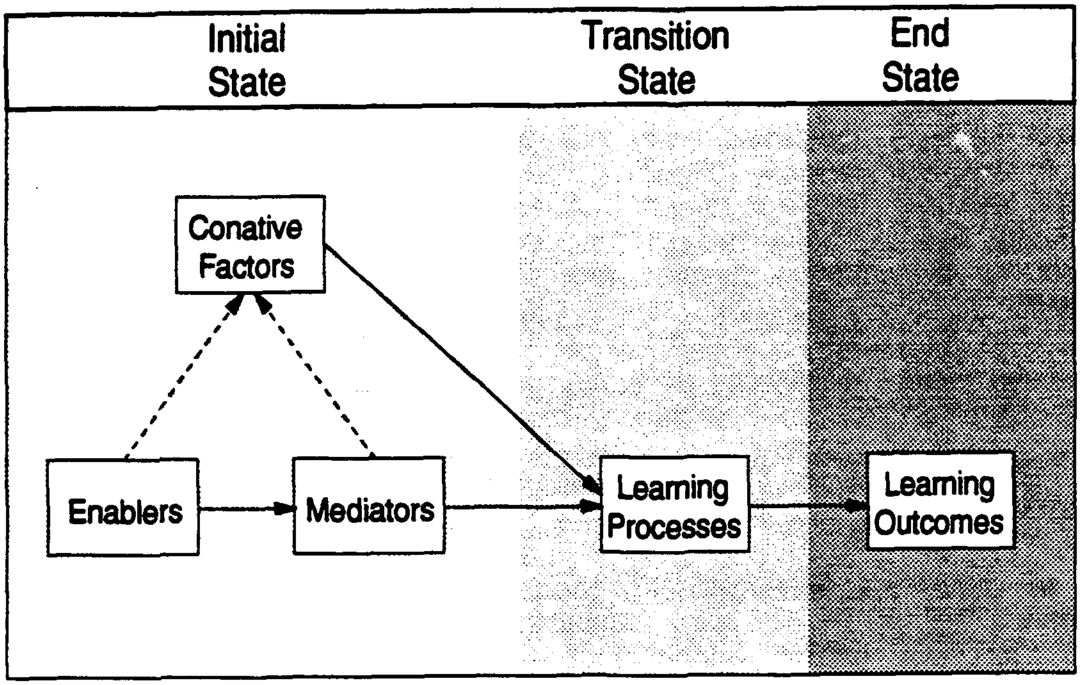


**Figure 1**
**Simple Model of Learning**

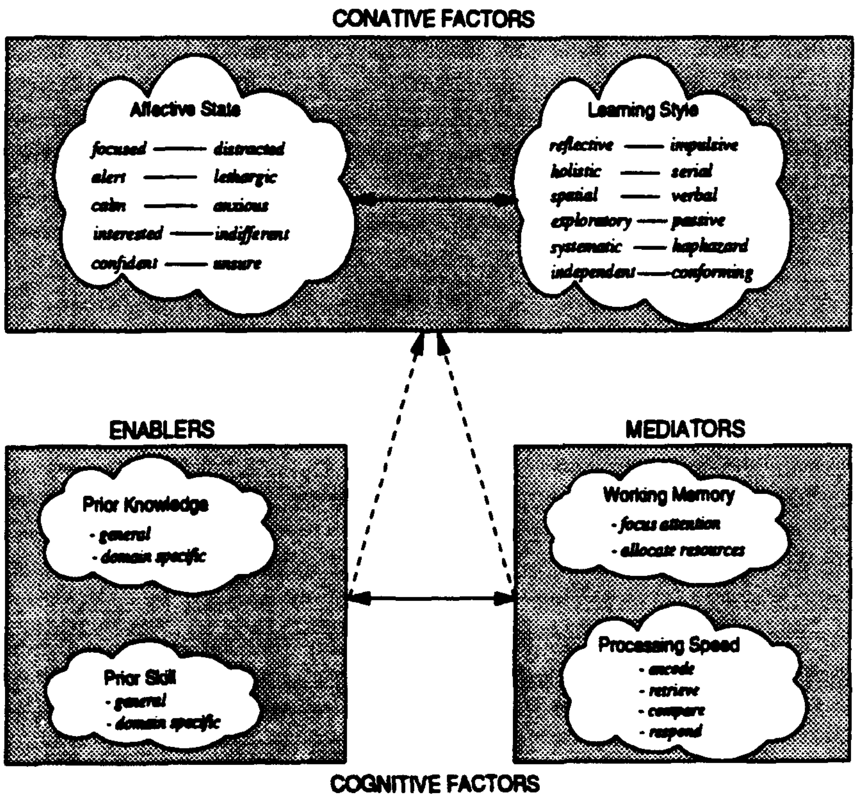


**Figure 2**
**Initial States**

## Conative Factors

When learning something new, individuals need to focus their attention and persist in the task, despite difficulties they may encounter. Individual differences in these learning activities reflect motivational or affective as well as learning style differences. These two categories have been clustered together under the heading of "conative factors" representing separate but correlated learner attributes.

*Affective state*, in general, describes an individual's bevy of feelings, attitudes and emotions distinct from cognition, thought, and behaviors. Affective states may be altered by external conditions (e.g., a pending exam affecting anxiety) or internal conditions (e.g., sleep deprivation affecting arousal). The affective state of the learner, regardless of the causal agent(s), can have a profound influence on learning or performance. To illustrate, Yerkes & Dodson (1908) found an interesting (inverted U-shaped) relation between arousal/anxiety and performance. Foot shocks were administered to subjects while learning a visual discrimination task (which ranged from easy to difficult). When the task was easy, increasing the shock level (and thus the anxiety level) actually increased performance on the task. But when the task became more difficult, a negative relation was found between shock level and performance. Optimal performance was associated with moderate levels of foot shocks.

Meier & Schmeck (1985) investigated the relationship between a general, negative affective state and several learning processes. They found that college students with higher scores on a "burned out" inventory showed significantly lower scores on measures of deep processing, elaborative processing, and fact retention. Another study investigated the general relationship between arousal and deep processing (Schmeck & Spofford, 1982). In this case, arousal was negatively associated with deep processing.

A series of studies reported by Revelle (1989) examined the relationship between affect and learning processes during performance on various learning tasks. For example, when a modified Sternberg (1969) memory-search task was used and an individual's affective state (arousal) was manipulated by the administration of caffeine, learning processes were shown to be differentially affected. Some processes were facilitated by caffeine intake (e.g., reduced reaction times to respond to items) while others were impaired (e.g., increased latencies associated with processing items in short-term memory such as encoding and comparing stimuli).

Another study reported by Revelle (1989) separated subjects into either "high impulsive" or "low impulsive" categories and found the following: High-impulsive subjects showed a *positive* relationship between arousal and performance on several ability tests. On the other hand, "low impulsive" subjects showed a quadratic trend where greater arousal was positively related to performance, but just up to a point, then too much arousal was found to be detrimental to performance. One possible explanation to account for these findings is that more impulsive individuals are generally less focused (more

easily distracted); therefore, when arousal levels are increased (e.g., with caffeine), this helps to focus their attention to the task at hand. Individuals who are less impulsive (and perhaps more reflective and focused) are facilitated up to a point by arousal, but too much arousal could actually be disruptive to the learning processes.

In summary, affective states can facilitate or impair learning processes, overall. Some affective states exert their influence on particular learning processes, while some have been shown to interact with other learner traits (i.e., learning styles like impulsivity) to impact learning. Let's now consider in more detail the second conative factor--learning style.

*Learning styles*, in the broadest sense, refer to "general behavioral dispositions that characterize performance on mental tasks; they are intellectual personality traits." (Baron, 1985, p. 366). They can be viewed as parameters of thinking, under voluntary control, and with optimum levels for a particular situation. For instance, being "reflective" is often a positive mental trait, but in some cases (e.g., a vigilance task requiring rapid responses), persisting in this style can be detrimental to performance. Whereas affective states can be easily manipulated and thus are more transitory in nature, learning styles are comparatively more stable. However, style does imply a choice by the learner as to preferred orientation towards learning, so it, too, should be manipulable through instruction or other environmental influences.

The learning styles in the list of exemplars shown in Figure 2 include: Reflective vs. impulsive, holistic vs. serial, spatial vs. verbal, exploratory vs. passive, systematic vs. haphazard, and independent vs. conforming. These styles have been synthesized from several sources (Baron, 1985; Kyllonen & Shute, 1989; Pask & Scott, 1972; Perrig & Kintsch, 1984; Shute, in press-a; Shute & Glaser, 1990) and represent commonly researched styles in the literature. This list should not, however, be viewed as exhaustive.

Probably the most researched learning style measure is reflectivity-impulsivity. Basically, this dimension represents the tendency to be accurate at the expense of speed in learning or problem-solving situations. That is, slower, more accurate processing is equated with a *reflective style* while faster, less accurate processing is associated with an *impulsive style*. Messer (1976) found a negative correlation between impulsivity and IQ. And when IQ was held constant, an inverse relationship still existed between impulsivity and school performance. Impulsive individuals, then, may not be allocating sufficient time for processing information during the learning process, thereby negatively impacting learning outcome.

Another study investigated the relationship between learning style and learning from a microworld environment (i.e., Smithtown). Shute & Glaser (1990) used a cluster analysis technique to characterize learners according to their performance indicators. Findings showed that individuals classified as *systematic* in their explorations of Smithtown (e.g., generating and testing hypotheses, replicating experiments) learned significantly more economic concepts compared to less systematic learners. Furthermore, systematic subjects tended to be more

reflective, taking time to collect and analyze sufficient data before deriving conclusions. Less systematic subjects were more impulsive and attempted to induce generalizations based on inadequate data. This learning style measure was also shown to be significantly correlated with general intelligence indicating that the more intelligent subjects tended to be more systematic and reflective. It is noteworthy that the intelligence measure only accounted for a small proportion (<1%) of unique learning outcome variance (i.e., total number of economic concepts acquired). In contrast, a particular learning style measure (i.e., hypothesis-driven behaviors or systematic style) accounted for a much larger proportion of outcome variance (38%). So, this systematic learning style and its associated learning processes can successfully predict learning in this type of environment.

Another learning style dimension that has been investigated is "holistic" vs. "serial." Pask & Scott (1972) identified these two types of learning styles and found the following: Holistic subjects were inclined to focus on higher-order relations and remembered the overall organization (or gist) of the subject matter to be learned. In contrast, subjects showing a serial style of learning tended to focus on lower-order relations and remembered information in lists. Pask and Scott showed that when a learning task was presented in a way that matched the learner's style (e.g., lists administered to serial subjects), then learning was enhanced.

In summary, these findings suggest that learning styles are associated with *different learning processes (e.g., serial learning style* with associative learning processes, systematic learning style with hypothesis-generating and testing processes). Learning processes may differentially affect learning outcome. Some learning styles affect learning processes which produce *quantitatively* different outcomes (e.g., reflective learners may encode and store more information and thus learn more). Other styles may affect learning *qualitatively* (e.g., spatial vs. verbal representations will result in different relationships learned). As discussed earlier, some learning styles interact with affective measures to differentially affect learning (e.g., Revelle, 1989 on arousal, impulsivity, and performance).

**Cognitive Factors**

As just discussed, learning is partly a function of a person's affective state and learning style. However, prior knowledge, skills, and cognitive abilities appear to be more reliable and robust predictors of learning (e.g., Shute & Kyllonen, 1990; Shute, Woltz, & Regian, 1989). Collectively, these fairly fixed characteristics of an individual's information-processing system comprise the cognitive factors that govern knowledge and skill acquisition. These cognitive factors have been separated into what Kyllonen and Christal (1989) have referred to as "enablers" and "mediators" of learning.

*Enablers* consist of what one already knows and can transfer to new situations. In particular, enablers refer to the depth, breadth, accessibility, and

organization of the knowledge possessed by a learner.[1] In fact, some researchers have argued that an individual's knowledge structure is the primary determinant of new learning (e.g., Chi, Glaser, & Rees, 1982; Schmalhofer, 1982; Walker, 1987; White & Frederiksen, 1986).

During the course of learning, components of new knowledge become interwoven with old knowledge; associations are established. A richer, more organized knowledge structure makes it easier to find "hooks" on which to hang new knowledge. Thus, high-knowledge individuals[2] can acquire and access larger chunks of information compared to low-knowledge individuals whose acquisition process is more piecemeal, and accessibility is often a problem (Chase & Simon, 1973; de Groot, 1966). The degree to which an individual's knowledge structure is organized impacts both the speed and accuracy by which new knowledge and skills are acquired (i.e., the learning processes). Glaser & Bassock (1989) have summarized this relationship as follows, "... structured knowledge enables inference capabilities, assists in the elaboration of new information, and enhances retrieval. It provides potential links between stored knowledge and incoming information, which facilitate learning and problem solving" (p. 26).

*Mediators* can be viewed as parameters that determine what one can acquire. They represent limits on the maintenance, storage, and retrieval of information, and thus govern the rate and quality of knowledge and skill acquisition. Examples of mediators include working-memory capacity and information processing speed.

Working memory, in general, is defined as the temporary storage, or activation level, of information being processed in a variety of cognitive tasks (e.g., Anderson, 1983; Baddeley, 1986). Two processes that are associated with this measure include: (1) focusing attention, and (2) allocating cognitive resources. Working-memory capacity has repeatedly been shown to be a potent predictor of learning across many and varied learning tasks (e.g., Ackerman, 1988; Kyllonen & Christal, 1990; Shute, 1991-a; Woltz, 1988). For example, Woltz (1988) found that during the early stages of skill acquisition, working-memory capacity is the most important determinant of successful learning. On the other hand, information processing speed plays an important role later in the learning process, after the task has been well practiced (e.g., Ackerman, 1988). Furthermore, if subjects are prevented from proceduralizing task knowledge, then working memory demands remain high, and working-memory capacity continues to be a strong determinant of task success, regardless of how much practice subjects have (Ackerman, 1986). Working-memory capacity has also been shown to be an important predictor of successful learning of a logic gates

[1]Figure 2 displays two categories of enablers: prior knowledge and prior skills. In this article, I refer to both incoming knowledge and cognitive skills as "prior knowledge." The reason is because incoming knowledge relates to declarative <u>knowledge</u> while cognitive skill relates to procedural <u>knowledge</u>, so both can be subsumed under "prior knowledge."

[2]High-knowledge may refer to having either a large amount of general knowledge (i.e., the breadth issue) or a large amount of specific knowledge (i.e., the depth issue).

task (Kyllonen & Stephens, 1989) and PASCAL programming skills (Shute & Kyllonen, 1990). In those studies, a working-memory factor predicted *all* phases of learning.

The second mediator, information processing speed, refers to the rate by which learners acquire new knowledge or skills. The affiliated processes for this cognitive measure include: encoding, storing, retrieving, comparing, and responding to information. While these processes tend to be fairly independent, they are relatively stable across content areas. That is, fast encoders may be slow retrievers, but fast encoders on a word task tend to be fast encoders on a numeric task (Kyllonen & Christal, 1989).

Is there a relationship between these two mediators? One possible link between working memory and information processing speed is that both of these measures reflect the dynamic activation level of a memory trace (Woltz, 1988). So, an individual with greater working-memory capacity (i.e., possessing an ability to establish and maintain activation levels) may process information faster because the relevant traces in long-term memory are already activated, thereby accelerating the search and retrieval processes.

Another relationship exists between the enablers and mediators. As learning progresses, knowledge becomes organized into larger, more coherent chunks of information. One consequence of this increased organization is that the process of retrieving information from long-term memory is more efficient (i.e., faster and more accurate). Moreover, working memory, dealing with chunks rather than isolated units of knowledge, can handle more information and thus has greater virtual capacity.

### Interaction Between Conative and Cognitive Factors

In addition to the main effects of conative and cognitive processes on learning, some research suggests there may be interactions between these factors (Gagné & Fleishman, 1959; Kanfer & Ackerman, 1989; Pinder, 1984; Vroom, 1964). For example, Vroom (1964) found that low motivation levels did not differentially affect performance for low or high ability subjects on a learning task. However, high motivation levels did differentiate performance based on ability level.

More recently, Kanfer & Ackerman (1989) found that motivation affected learning differentially during the learning process. When subjects engaged motivational processes too early (i.e., before the acquisition of declarative knowledge), learning was impeded because resources were allocated toward motivational, self-regulatory processes and away from learning the task at hand. But when motivational processes were engaged later during the course of learning (when cognitive processes were less occupied with the learning task), results indicated a facilitative effect of motivation on learning.

Finally, a number of studies cited by Snow (1989) involve conative and cognitive aptitude interactions in learning. For example, one study described a significant relationship involving (a) interest in school subjects, (b) cognitive abilities, and (c) achievement. Findings showed that more interest was associated with higher cognitive ability measures, and both predicted achievement. What is unclear is whether individuals develop abilities in areas of high interest, or whether interests develop as a result of exercising abilities in a given area. But regardless of the direction of influence, the conative-cognitive correlation exists.

## LEARNING PROCESSES

The simplest relationship between learning process and outcome has been summarized by Bower and Hilgard (1981) "... as a process is to its result, as acquiring is to a possession, as painting is to a picture" (p. 1). But painters differ--they have diverse experiences, use different painting techniques, and thus produce quite different pictures.

In general, learning processes may be defined as any series of actions or changes that directly impact the learning outcome. The definition used here will be limited to the processes related to: associative learning, procedural learning, and inductive reasoning. These three processes are arrayed along a dimension of increasing complexity where associative learning processes represent more elementary ones, followed by the procedural learning processes, and ending with the more complex processes involved with inductive reasoning. Furthermore, these three categories are influenced, or controlled, by a fourth process: metacognitive skills. Figure 3 shows the organization of the learning processes focused on in this article.

### Metacognition

A variety of terms in the literature are used to refer to metacognition (e.g., self-regulatory processes, learning strategies, control processes, executive skills). For our purposes, metacognition is defined as personal knowledge of one's learning abilities and limitations, including skills that enable the acquisition, application, and control of knowledge and skills. The specific processes included under this construct have been assembled from the voluminous research in this area (e.g., see Baron, 1985; Brown, 1978, 1987; Brown & Palinscar, 1974; Collins & Stevens, 1982; Flavell, Friedricks, & Hoyt, 1970; Glaser & Bassock, 1989; Kanfer & Ackerman, 1989; Kuhl & Kraska, 1989; Schmeck, 1988). These processes include: (a) defining the problem or goal into one's own words; (b) developing a plan to attain that goal; (c) allocating resources (e.g., time, processes) for enacting the plan; (d) executing the plan; (e) monitoring progress (or identifying problem areas and thus modifying the plan); and (f) summarizing and integrating results (new knowledge or skill) into the existing knowledge structure. This whole series of actions may be performed over and over again

because most learning tasks can be decomposed into smaller, more manageable problems or goals.

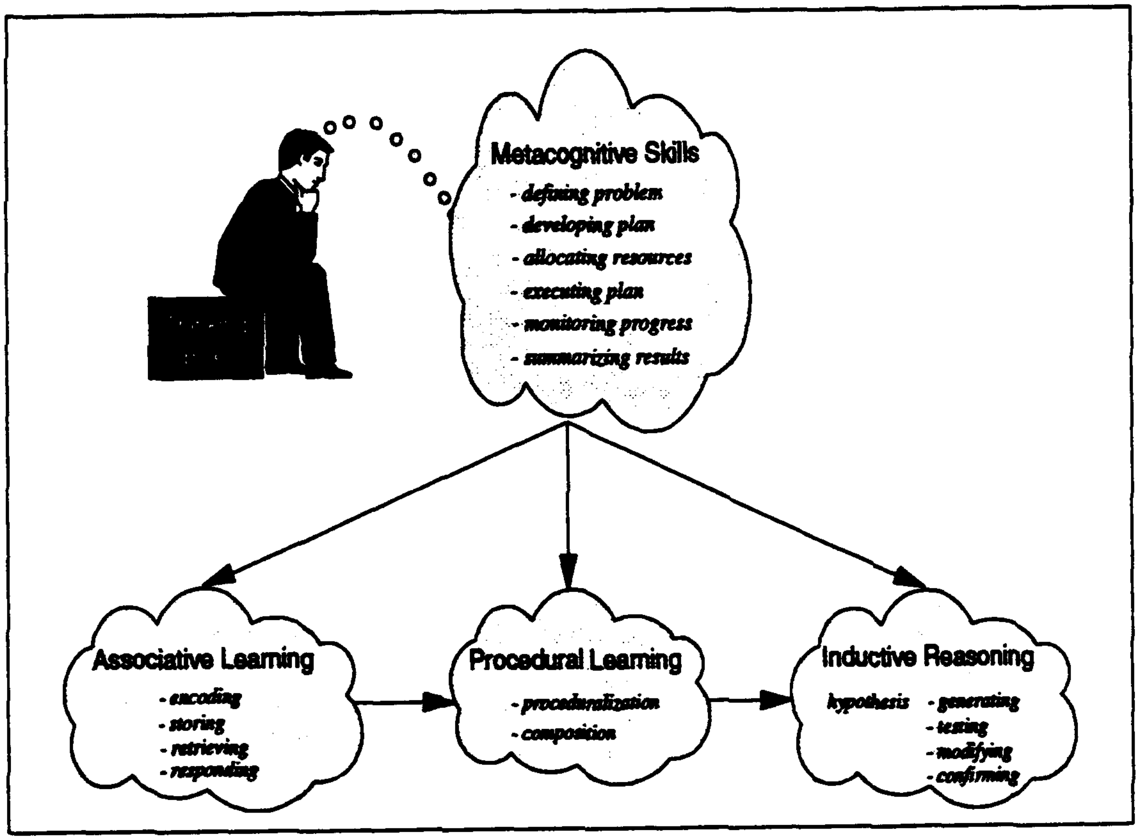


**Figure 3**
**Learning Processes**

Metacognitive skills typically begin to appear between the ages of 6 to 10 years old (Kuhl & Kraska, 1989). Not all of these processes arise at the same time. For instance, it is cognitively easier to define a particular problem than to be able to actually design an effective plan to solve the problem. Flavell et al. (1970) presented a set of items for children (kindergarten to fourth grade) to memorize. Findings showed that older children *knew* when they had succeeded in memorizing the set, and their recall performance supported their perceptions. In contrast, when younger children indicated they had memorized the items, their actual recall performance was faulty. So, the older children were able to define the problem (memorize list), develop a plan (rote memorization or elaboration), allocate resources (allow enough time to complete the list), execute the plan (begin encoding process), monitor progress (self-check on memory of items), and summarize results (indicate readiness when list could be recalled without prompts). Younger children could specify the goal of the task, but were mostly unsuccessful in applying the other metacognitive skills, and thus unsuccessful in their outcome performance.

In addition to developmental differences in metacognition, there are individual differences as well. The source of these differences probably resides in the underlying cognitive and conative aptitudes. For example, Brown (1978) has reported that retarded children show severe impairments with regard to exercising most metacognitive skills. However, even deficit performance evidenced by retarded persons in memorization can be partly overcome through instruction in certain strategies, such as rehearsal (e.g., Belmont & Butterfield, 1971).

Other studies focusing on training metacognitive skills have succeeded in consequently enhancing skills in the following areas: reading comprehension (e.g., Brown & Palinscar, 1984), math (e.g., Schoenfeld, 1985), writing (Scardemalia, Bereiter, & Steinbach, 1984), and microeconomics (Shute, Glaser, & Raghavan, 1989). The importance of these findings is that effective metacognitive skills influence learning in a variety of domains. This learning probably occurs at the level of the learning processes, which will now be discussed.

**Associative Learning**

The processes affiliated with associative learning are believed to represent *fundamental* learning abilities, involving the rate and quality of forming associations or links between new and old knowledge. The notion that associative learning processes are general and important to knowledge and skill acquisition is certainly not new. Rather, the literature offers ample support for this proposition (e.g., Anderson, 1983; Kyllonen & Tirre, 1988; Malmi, Underwood & Carroll, 1979; Underwood, 1975). The processes believed to constitute associative learning are: encoding, storing, retrieving, and responding to information from the environment. These processes are mediated by the cognitive and conative factors, discussed earlier. For instance, the speed and accuracy of encoding a new unit of information are constrained by an individual's processing speed and also working-memory capacity.

**Procedural Learning**

Since the turn of the century, psychologists have been interested in studying procedural learning (or skill acquisition) distinct from fact learning (see Bryan & Harter, 1899). This distinction continues to intrigue cognitive psychologists today. A procedure is defined as any unit of knowledge represented in the form of if-then rules. Procedures may be general (e.g., how to work backwards from a goal) or specific (e.g., how to measure the diameter of a circle).

Unlike associative learning, which is characterized by the processes related to acquiring facts, procedural learning is characterized by the processes related to compiling procedures or rules into efficient skills (i.e., knowledge compilation). According to Anderson (1987), knowledge compilation actually consists of two related processes. *Proceduralization* transforms a general rule into one that is specialized for a particular task. So the general procedure serves as a template

for the formation of a more domain-specific production or rule. *Composition* is a related process pertaining to the collapse of a sequence of lower-level rules into a larger, more complex rule. Finally, productions are strengthened as a result of sustained and successful practice applying them.

## Inductive Reasoning

While both associative and procedural learning involve the acquisition of some information at hand, inductive reasoning transcends given information. It involves the *discovery* of rules and principles, requiring greater mental effort on the learner's part than simply encoding or proceduralizing knowledge. While inductive reasoning is a complex learning process, it has been argued that it represents a primary mental ability (e.g., Thurstone, 1938).

Typically, inductive reasoning is invoked given a set of problems or examples from which specific rules must be derived and applied in the solution of subsequent problems. To illustrate inductive reasoning processes, please attempt to solve the problem shown in Figure 4. This example is similar to actual items found on the Raven's Progressive Matrices test. The task characteristics require abilities in generating and testing hypotheses fitting a given set of data (e.g., progressions of geometric stimuli), as well as modifying hypotheses if the test is not confirmed. Simple introspection should validate the proposed processes (i.e., generating, testing, and modifying various hypotheses before arriving at the *correct solution*).

The higher-level processes of developing and testing hypotheses can be decomposed into lower-level processes. First, the various attributes of the data or stimuli must be *encoded* (e.g., vertical bar shadings in Figure 4). After that, one needs to systematically analyze or *compare* the ways in which individual stimuli relate to one another. Only then may a hypothesis be generated, establishing a possible relationship among attributes. One of the most difficult aspects of inductive reasoning is maintaining a growing number of relationships or rules in working memory, thus there is a direct relationship between working-memory capacity and inductive reasoning skills (see Kyllonen & Christal, 1990 for more on this topic). Finally, individual differences in inductive reasoning exist both developmentally as well as within comparable age groups (e.g., Goldman, Pellegrino, Parseghian, & Sallis, 1982; Kyllonen & Christal, 1990; Pellegrino, 1985; Sternberg, 1977).

In summary, four learning processes have been postulated to directly impact learning: *metacognitive skills*, *associative learning*, *procedural learning*, and *inductive reasoning*. Individual differences in the application of these processes are believed to be what determines the learning outcome, discussed next.

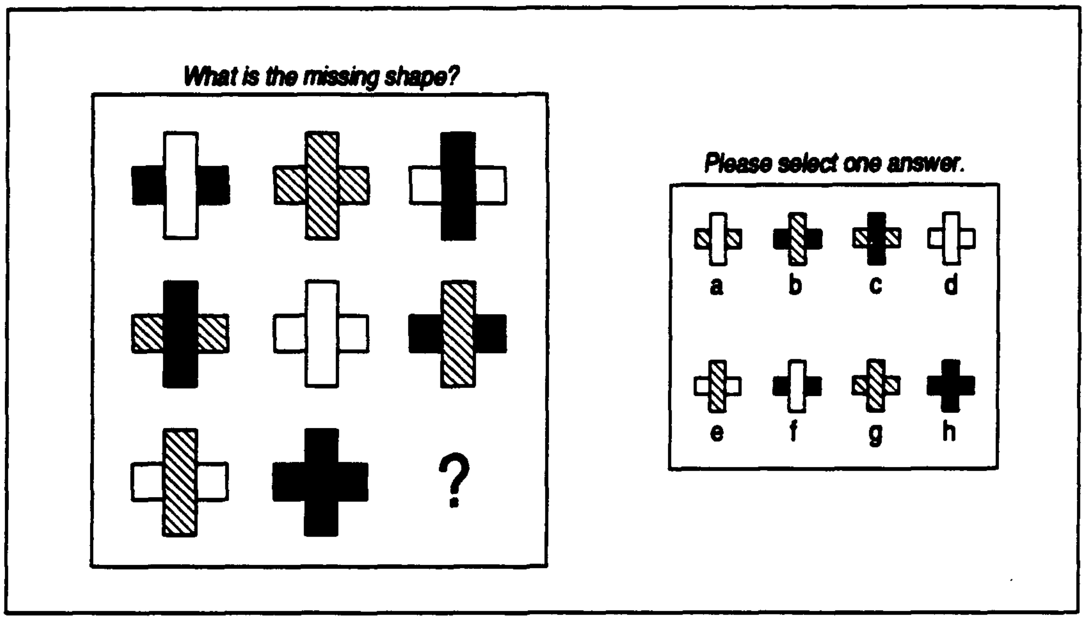


**Figure 4**
**Example Inductive Reasoning Test Item**

## LEARNING OUTCOMES

The outcome of learning, as the name implies, refers to what the learner walks away with from a learning task. One way to characterize the wide assortment of learning outcomes can be seen in Figure 5. Here, the declarative-procedural distinction is fundamental; a learner will usually acquire, to some degree, new knowledge or new skill from a learning task. Furthermore, refinements are made within each of these two categories. Declarative knowledge can be arrayed by complexity, from propositional knowledge, to schemata (collection of related propositions), to mental models (collection of functionally or conceptually related schemata). Similarly, procedural knowledge can be arrayed from simple rules or productions, to skills (collection of related productions), to automatic skills (skills executed without conscious attention) (Kyllonen & Shute, 1989). Figure 5 represents the learning outcomes focused on in this article.

### Declarative Knowledge Outcomes

A *proposition* is the basic unit of knowledge; a single, isolated postulate (e.g., Gasoline serves as fuel for automobiles.). A *schema* is an interconnected set of related propositions and concepts defining a situation (e.g., Fuel is combustible; spark plugs convert electrical current across metal points into sparks; sparks ignite fuel.). The most organized declarative knowledge structure is the *mental model*, a highly organized set of related propositions, concepts,

and rules representing some integrated system (e.g., Fuel lines feed gasoline to the area of the spark plugs. Spark plugs receive energy from the distributor or electronic ignition causing a spark to occur. The spark ignites the fuel causing it to explode in a controlled manner. The explosion drives the piston down, and the descending piston drives another piston up and also creates a vacuum causing more fuel to enter the area. Pistons going up and down rotate the crank shaft, and this mechanical energy is used to drive the car.).

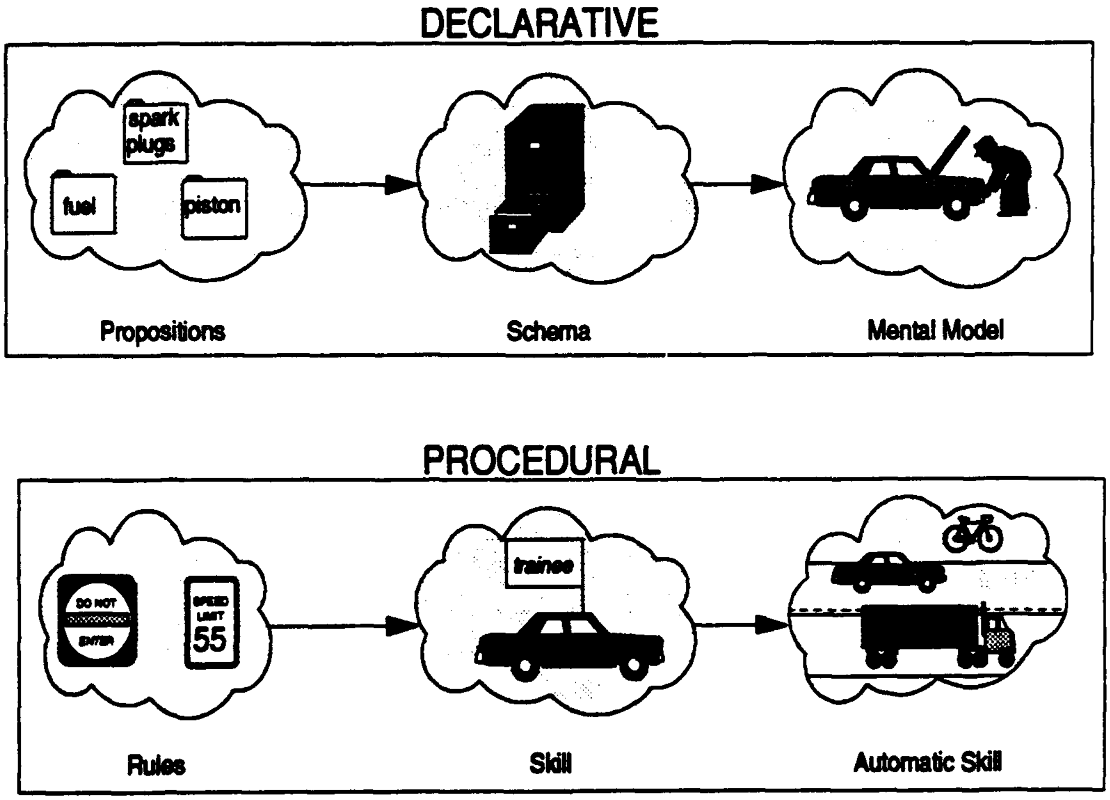


**Figure 5**
**Learning Outcomes**

## Procedural Skill Outcomes

A *rule* is the basic unit of action, a representation of a condition-action pair. The condition may be defined in terms of cognitive or perceptual states while the action may be cognitive or motor (e.g., If you are driving and want to turn left, then turn on the left turn signal and glance to the left.). A skill is a collection of related rules and can be cognitive, perceptual, or motor (e.g., driving a car in traffic). Finally, a skill may become an automatic skill only after considerable practice applying that skill in many and varied situations, eventually requiring little or no conscious effort. Most skills involve both cognitive and perceptual conditions and both cognitive and motor actions (e.g., executing a left turn off of a highway by automatically turning on the turn signal and

glancing to the left, adjusting the steering and acceleration of the car as necessary, while simultaneously listening to the radio and planning the menu for the evening's meal).

So, the desired learning outcome may be declarative or procedural in nature and may further be distinguished by level of complexity. For instance, the learning outcome for a Russian history course would most likely be declarative knowledge, and could range from propositional knowledge of historical facts to a mental model of the flow of events in Russian history with associated, causal factors. On the other hand, the learning outcome for a computer programming course would probably be procedural skills enabling learners to write executable programming code. It is important that learning outcome measures actually correspond to the desired goals of the course. Otherwise, there would be a mismatch between what is instructed and what is being assessed. Let us now consider the numerous methods that exist to impart knowledge and skills.

## LEARNING ENVIRONMENTS

One useful way to characterize learning environments (especially computerized environments) is in terms of the amount of learner control supported during the learning process.[3] Environments can be viewed as a continuum ranging from minimal (e.g., rote or didactic environments) to almost complete learner control (e.g., discovery environments). See Figure 6 for an illustration of learning environments examined in this article.[4] There is considerable debate in the literature concerning what constitutes an optimal learning environment, especially related to computerized instruction. At one end, some have argued that it is better to develop straightforward, more didactic, learning environments that do not permit excessive digressions from an optimal solution path (e.g., Anderson, Boyle & Reiser, 1985; Corbett and Anderson, 1989; Sleeman, Kelly, Martinak, Ward, & Moore, 1989). The other end argues for more unstructured learning environments containing adequate tools for the learner to employ during the learning process (e.g., Collins & Brown, 1988; Shute, Glaser, & Raghavan, 1989; White & Horowitz, 1987). But the issue is really more complicated than simply which is the better learning environment; rather, a more helpful question is: Which is the better environment for what type(s) of persons, a classic aptitude-treatment interaction question (Cronbach and Snow, 1977). This issue will now be examined in more detail.

[3] This dimension was originally derived from a taxonomy of machine learning research synthesized from Michalski (1986) and Carbonell et al. (1983) and elaborated on in Kyllonen and Shute (1989).

[4] Figure from Kyllonen (1992), A generic model of learning. Paper presented to the Air Force Academy, Colorado Springs, CO (reprinted by permission).

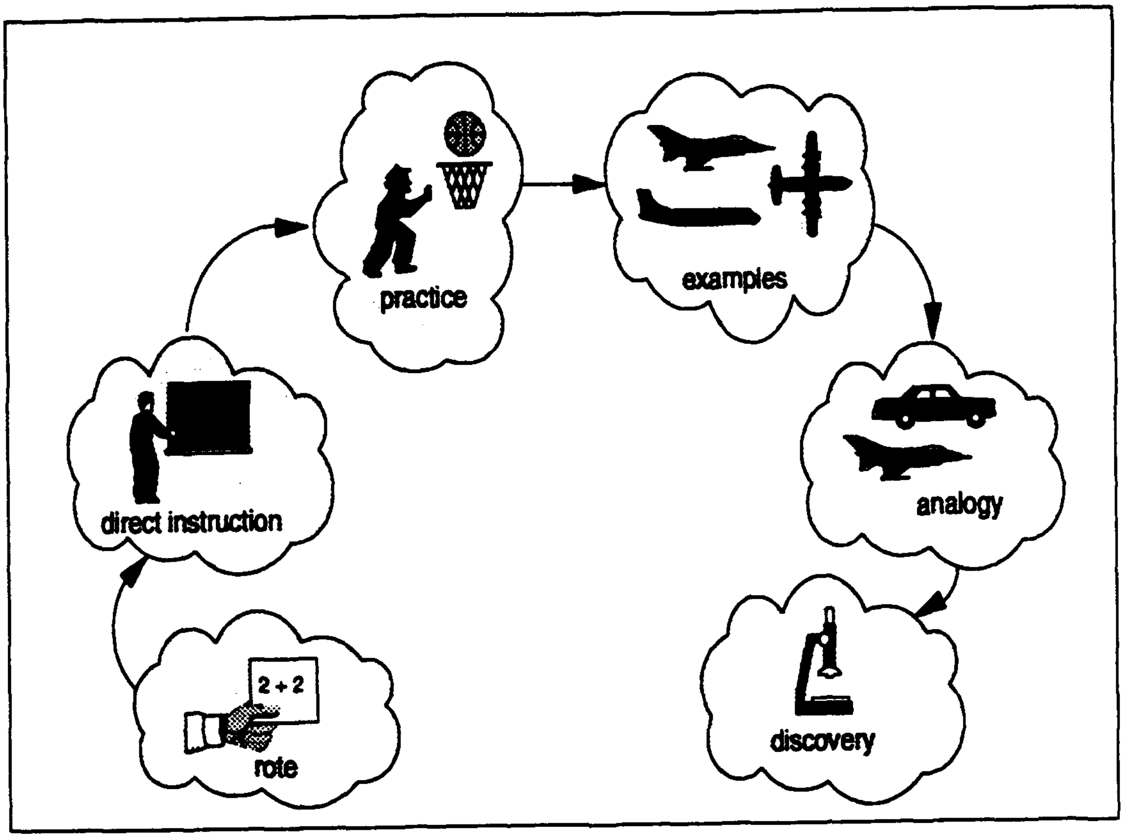


**Figure 6**
**Learning Environments**

## INDIVIDUALIZED INSTRUCTION AND APTITUDE-TREATMENT INTERACTION RESEARCH

The idea that teaching is best accomplished by tailoring instruction to individual learners is not new. For example, Snow & Yallow (1982) point out that in an ancient Hebrew reference, the Haggadah of Passover, four sons with differing characteristics are portrayed: wise, wicked, simpleminded, and one that asks no questions. The Haggadah describes four different ways to teach the meaning of Passover to each kind of son. Today, this idea of individualized instruction forms the basis of several important streams of research, such as *mastery learning* (e.g., Bloom, 1956; 1984; Cohen, Kulik & Kulik, 1982), *aptitude-treatment interactions* (e.g., Cronbach & Snow, 1977; Shute, in press-a; in press-b), and *intelligent tutoring systems* (e.g., Burton & Brown, 1982; Mandel & Lesgold, 1988). The idea also has empirical support. A certain amount of data indicate that carefully individualized instruction is superior to conventional group instruction (for reviews, see Bloom, 1984; Kulik, Kulik, & Bangert-Drowns, 1990; Shute, 1991-b). But what characteristics of a learner should the computer (or teacher) assess in order to personalize (and thus optimize) instruction?

## ASSOCIATIVE LEARNING BY ENVIRONMENT INTERACTION

Shute (in press-b) conducted a study using an intelligent tutoring system (ITS) instructing basic principles of electricity. Over 300 subjects participated in the study. First they completed a computerized battery of cognitive tests which measured associative learning skills as well as other cognitive abilities,[5] then were randomly assigned to one of two learning environments: rule induction or rule application. The two learning environments were created from the one tutor by altering the nature of the feedback to the learner, everything else remained the same. The computer presented all problems (under both learning conditions) by showing different electrical circuits and asking questions about them. After completing a problem, all subjects received feedback concerning whether their answer was correct. The relevant principle was addressed in one of two ways. In the rule application environment, feedback clearly stated the variables and their relationships for a given problem (e.g., "*The principle involved in this kind of problem is that current before a resistor is equal to the current after a resistor in a parallel net.*"). Subjects then proceeded to apply the rule in the solution of related problems. But in the rule induction environment, the tutor provided feedback which identified the relevant variables in the problem, but the learner had to induce the relationships among those variables (e.g., "*What you need to know to solve this type of problem is how current behaves, both before and after a resistor, in a parallel net.*"). Subjects in the rule induction condition, therefore, generated their own interpretation of the functional relationships among variables comprising the different rules.

Four posttests were administered to subjects after they had completed the curriculum (25 principles, averaging about 12 hours of learning time spanning 2-3 days). The first two tests measured declarative knowledge and the last two tests measured procedural skill acquisition. Figure 7 shows the results from this study.

Results showed the following pattern of interactions involving associative learning skills, learning environment, and type of outcome measured.

*Declarative knowledge outcome*: (1) Subjects with higher measures of associative learning (AL) skills learned more if they had been assigned to the rule induction environment, and (2) low AL subjects learned more if they had been assigned to the rule application environment.

*Procedural skill outcome*: (3) High AL subjects developed more skill if they had been assigned to the rule application environment, and (4) low AL subjects performed poorly on the procedural skills tests, regardless of learning environment.

[5]The CAM-4 battery of cognitive tests was used (Kyllonen, Christal, Woltz, Shute, Tirre & Chaiken, 1990). This battery measures: working-memory capacity, information-processing speed, associative learning, procedural learning, inductive reasoning, and general knowledge in each of three content areas: verbal, quantitative and spatial.

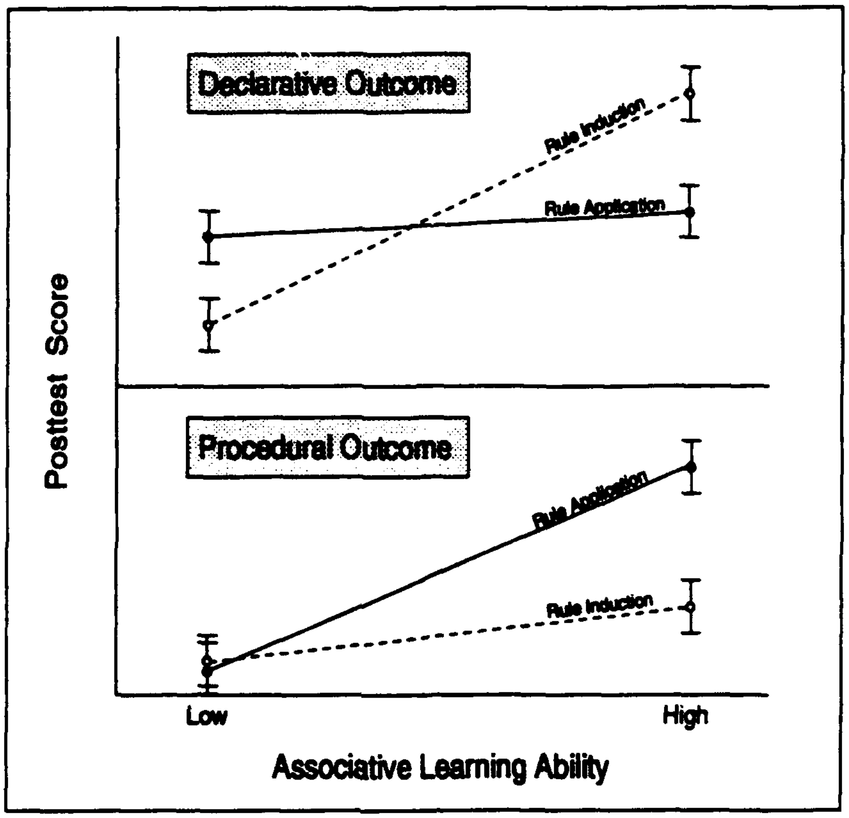


**Figure 7**
**Associative Learning by Environment Interaction**

The rule induction environment elicited declarative representations. Learners had to first understand the concepts involved in a given problem, then create a rule by connecting relevant concepts together in a meaningful way. Cognitive resources would thus be consumed by the processes, discussed earlier, relating to inductive reasoning (viz., generating and testing hypotheses). A possible explanation for the finding that high AL subjects in the inductive environment performed well on the declarative knowledge tests, is that there was a good match among learning environment, outcome measure, and cognitive ability: (1) the rule induction environment supported declarative representations; (2) the outcome tests required accessing declarative representations; and (3) the high AL subjects possessed relevant cognitive skills.

Another "match" accounted for the finding that high AL subjects in the application environment performed well on the procedural skill tests. The rule application environment simply informed learners of the appropriate rule underlying each problem. For related problems, learners promptly applied the rule during the solution process. The cognitive activity supported by this environment was the proceduralization of skills. Subjects with good associative learning skills performed well on the procedural skills tests in the applied environment because: (1) the application environment supported proceduralization of skills; (2) the

outcome tests required the application of rules and procedures in the solution of problems; and (3) the high AL subjects possessed good cognitive abilities.

Individuals with lower AL measures acquired more declarative knowledge from the tutor if they were in the rule application environment as opposed to the induction environment, probably because of its straightforward instructional approach (i.e., the explication of rules). Furthermore, these low ability subjects' deficient skills were not as burdened as they would have been in the induction environment. Because the computer provided the relevant rules explicitly (and repeatedly), this should have enabled memory for the associated principle, thus enhancing performance on the declarative knowledge tests. When the outcome being measured was procedural, however, neither learning environment enhanced outcome performance for low AL subjects. They scored equally poorly.

So, the more demanding rule induction environment simply does not "pay off," except if the outcome measures declarative knowledge acquisition. The rule application environment, in contrast, does not "waste" cognitive resources in the induction of variable relationships. By providing these relationships to subjects explicitly in the form of specific feedback, learners can proceed immediately to apply them across various circuits. To solve the more complex procedural skills tests, a learner must have had sufficient and consistent practice across a variety of circuit types. These findings are in accord with other research on practice and skill acquisition (e.g., Ackerman, 1988; Schneider & Shiffrin, 1977; Regian & Schneider, 1990).

## EXPLORATORY LEARNING STYLE BY ENVIRONMENT INTERACTION

Different data from the same study, described earlier, can be used to illustrate another ATI, namely *exploratory learning style* by environment interaction. The purpose of this investigation was to explore the possible interaction between a particular learning style measure and environment on the same outcome measures previously mentioned (see Shute, in press-a for more on this topic). It is hypothesized that an active, exploratory learning style (evidenced by a composite of certain behaviors) would facilitate knowledge and skill acquisition in conjunction with the environment supporting inductive learning behaviors. Less exploratory behaviors were hypothesized to be better suited to the structured learning environment. Figure 8 shows the results from this analysis.

As seen in Figure 8, the interaction hypothesis was supported. The disordinal interaction was straightforward: Two opposite trends defined the correlations between exploratory behavior and outcome score. A positive linear trend expressed the relationship between exploratory behavior and outcome in the rule induction environment (i.e., more exploratory behavior is associated with greater outcome scores in the induction environment). But a strong *negative* trend defined the relationship between exploratory behavior and outcome in the rule application environment (i.e., more exploratory behavior is associated with poorer outcome in the applied environment).

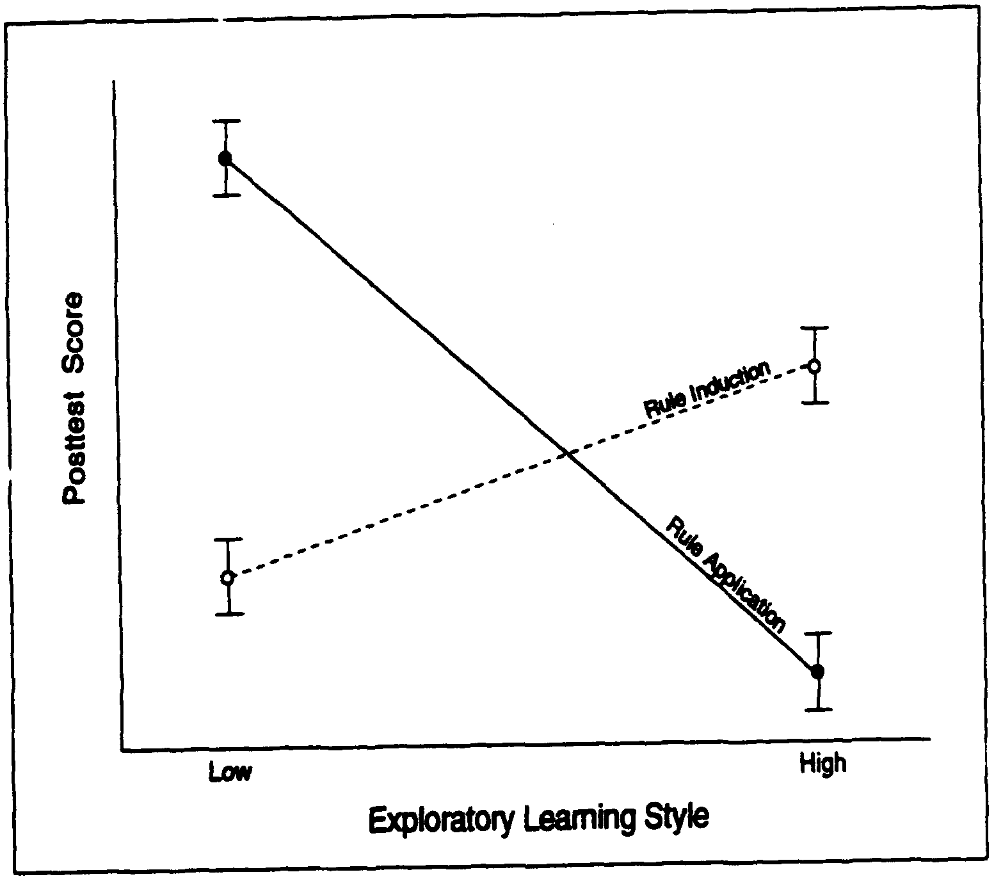


**Figure 8**
**Exploratory Learning Style by Environment Interaction**

The explanation for these findings again centers on matching learner and environment. Exploratory individuals thrived in the inductive environment but may have become bored in the directed environment, while less exploratory persons acquired more knowledge and skills from the structured environment. Furthermore, exploratory behavior does not appear to be an artifact of aptitude: the correlations between this learning style measure and various cognitive process measures were zero.

## CONCLUSION: A MODEL OF LEARNING

As stated earlier, the purpose of this article was to examine possible relations among initial states, learning processes, and learning environment on learning outcome measures in order to devise a model of learning. After defining and elaborating each major construct, results were presented supporting the notion that learning environments can impact learning outcome differentially, dependent on characteristics of the learner (e.g., associative learning processes and exploratory learning style).

For a model of learning to influence instructional psychology, it would require substantial empirically derived information, such as: how to implement the various learning environments; what learning outcomes are better suited to which types of environments; which aptitude measures interact with the learning environments; and so on. In addition, each outcome measure would need to contain detailed information about how to test for the presence and quality of various knowledge types (see Kyllonen & Shute, 1989). Over time, sufficiently detailed information could be assembled to guide the development of principled instruction across a wide range of curriculum goals.

A first attempt at outlining such a model appears in Figure 9 integrating the components discussed in this article and representing an expansion of the simple model depicted in Figure 1. Arrows in the figure represent real, as well as hypothetical, relationships among initial states, learning processes, learning outcomes, and learning environments--solid lines denoting more direct relations and dashed lines representing less direct relations.

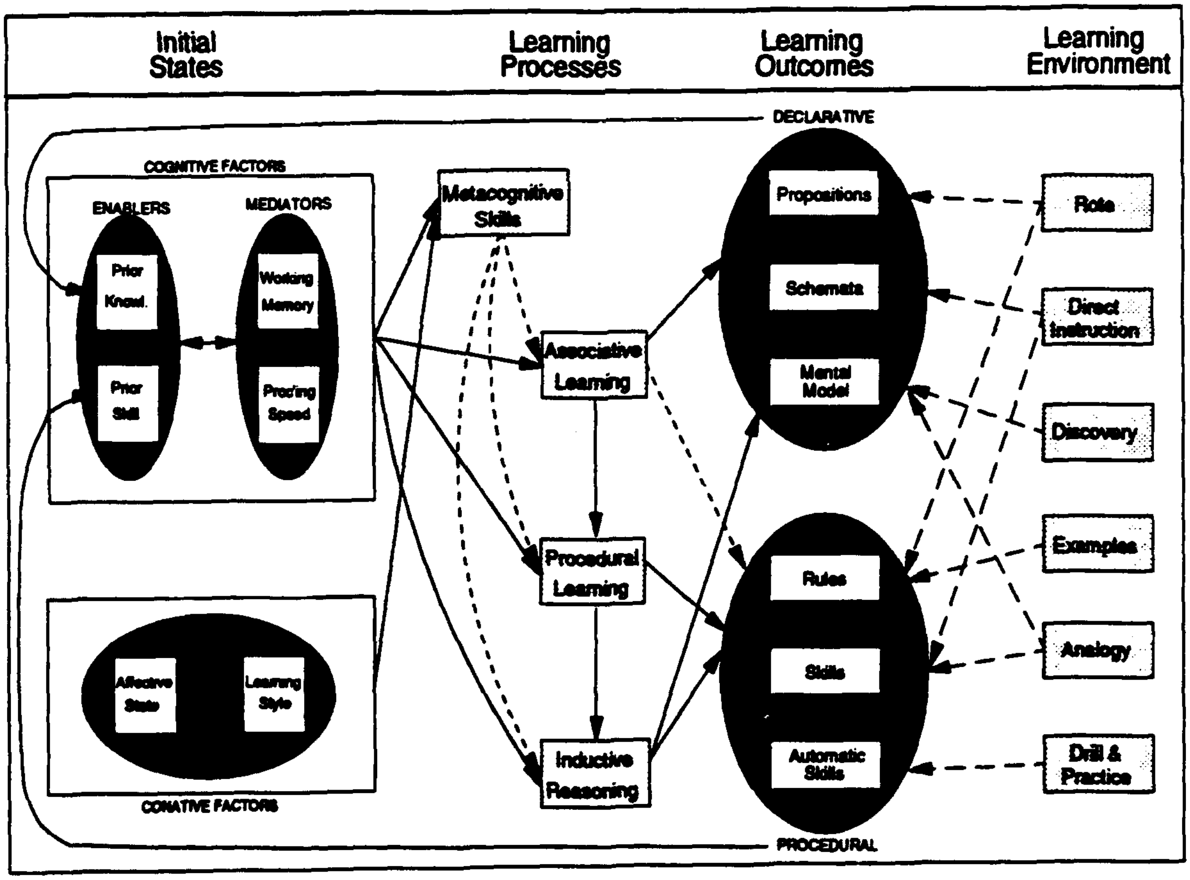


**Figure 9**
**Model of Learning**

This model shows the two main initial states (cognitive and conative factors) exerting an influence on the learning processes. In particular, the cognitive factors directly impact metacognitive skills, associative learning, procedural learning, and inductive reasoning. These relations have been documented in the literature. The conative factors, however, are depicted only impacting metacognitive skills, but other relationships are possible (e.g., impulsive learning style--> associative learning processes--> declarative outcome).

Among the learning processes, metacognitive skills have been shown to influence other learning processes. These three learning processes show specific relations to learning outcomes. First, associative learning is shown to directly influence declarative knowledge outcomes, but another possible (dashed line) relationship has been made to procedural learning. For example, rule-learning may be accomplished with associative learning skills. The processes underlying procedural learning are shown influencing procedural outcomes (e.g., facility in proceduralizing knowledge leads to the development and acquisition of skills). And finally, inductive reasoning processes are shown exerting influences on both declarative outcomes (e.g., formation of mental models) as well as procedural outcomes (e.g., induction of rules).

Learning outcomes are typically the end product of learning, but if a curriculum or learning task is broken down in a collection of learning outcomes, each new knowledge or skill acquired alters the initial state of the learner. That is, each new declarative or procedural outcome eventually becomes prior knowledge or skill when it becomes integrated into the existing knowledge structure.

The relationships among learning environments and outcomes is more speculative, thus a ripe area for additional research. For instance, initial learning of propositional knowledge or simple rules is probably best accomplished in environments supporting rote memorization. The acquisition of a mental model may be best supported by exploratory or discovery environments. Also, the development of automatic skills is probably better served by a drill and practice learning environment.

Finally, the area of most interest to the focus of this article involves the interaction among learner characteristics, learning environment, and outcome. For example, we saw that when the outcome was declarative knowledge, individuals with higher associative learning skills learned significantly more from the discovery (or rule-induction) environment. But when the outcome being assessed was procedural skill, individuals with higher associative learning skills learned better from the applied or directed environment. Furthermore, exploratory learners acquired more knowledge and skills if they had been assigned to the discovery environment, while less exploratory individuals learned better from the structured, directed learning environment.

In conclusion, the puzzle parts have been presented and a first effort has been made to relate the pieces together. Additional research is needed in the area to obtain information on both the direction and strength of the arrows

depicted in the proposed model of learning. Furthermore, a science of instruction need not be restricted to finding just one "optimal" learning environment. Rather, multiple environments working in concert may best serve the instructional needs of some curriculum and for different students at different times during the learning process.

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